A Study of Mobility in Ad Hoc Networks and its Effects on the Gradient Algorithm

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***Abstract*—The Gradient Algorithm is one of the basic elements for computing coordinate systems in GPS free environments. It is mainly used to estimate distances between devices but is prone to error. We define and analyze two error models to describe the origin of underestimated and overestimated distances. Different movement patterns are examined to get an understanding of their impact on the Gradient Algorithm. Our experiments and analysis indicate that mobility can have a positive effect on the accuracy of the algorithm by an emerging effect of asynchronous computation and fluctuating distribution of nodes. In addition, some parameters, such as direction and variance in movements, are identified that are responsible for the disparity in the influences of the presented mobility models.**

***Index Terms*—ad hoc networks; mobility; hop count; error analysis;**

I. Introduction

In many applications such as geographic monitoring, smart buildings, target tracking or disaster management, a large number of possibly mobile devices is utilized to accomplish a specific goal. In general, such devices consist of low power processors, have little memory and limited wireless communication range to exchange short messages with other devices. A network of such devices is called mobile ad hoc network (MANET) as the network's connectivity is dynamically and formed ad hoc. MANETs are widely studied in literature and there is even a working group founded by the Internet Engineering Task Force (IETF) to investigate related issues [1]. As bulks of such devices might be necessary to perform a task, they generally are assumed to be mass-produced, therefore inexpensive, and of small sizes. In such networks, there is often a trade-off between reliability and cost. Additionally, to avoid further expenses, the devices usually are not equipped with any localization techniques. This makes it hard to realize applications that depend on the location of each device such as pattern formation in an Amorphous Computer ([2], [3]), GeoRouting [4] or even a futuristic idea like the development of an Invisibility Cloak [5]. For that reason, different approaches like multilateration [6] or triangulation [7] have been proposed to build a coordinate system in an ad hoc network. These methods are based on a distance measuring process, often described as Gradient Algorithm [8], [9] sometimes referring to the chemical gradients observed in morphogenesis [10]. In this paper, we consider a mobile ad hoc network of many devices (nodes) and analyze the effects of different mobility models on the Gradient Algorithm (GA).

Previous observations [11] revealed that the GA for distance estimation works well in dense and evenly distributed networks. However, in sparse or irregular networks, the gradient provides no reliable distance estimation anymore which can lead to inadequate localization results. Our goal is to quantify the error of such a gradient derived distance estimation and investigate the impact of different mobility models on the applicability of a GA.

In this paper, we consider mobile devices which are not autonomous and cannot move by themselves like robots, but they are passive, i.e. they can be moved by people, animals, or nature. As the movement of devices in a mobile ad hoc network highly depends on the applications and environment a large spectrum of mobility models is analyzed here. Also, two different error types are identified in the GA for distance estimation caused by either the distribution of the devices or mobility.

Our observations and analysis indicate that many of the mobility models positively influence the error rate. Nevertheless, a high mobility can also increase the error turning the natural overestimation of the distance into an underestimation.

This paper is structured as follows. In section II, the basics and the problem are described as well as the related work concerning the distance estimation in ad hoc networks. In section III, the different mobility models are presented that will be examined in the experiments. Section V introduces the simulation environment as well as the experiment setting and shows the experiment results and interpretations. Section VI concludes the paper.

II. Basics

A. Model

Our model of an ad hoc network assumes randomly distributed mobile devices on a two dimensional obstacle free plane. The mobile devices do not have global knowledge of the topology or their location. Each device moves and can only communicate with the devices in its neighborhood. Collisions are not considered in the model. We define the neighborhood of a device as a physical neighborhood on the plane within a fixed distance r from the device. r is supposed to be much smaller than the dimensions of the plane. We assume that all

the devices have the same properties (homogeneous devices), except for a seed device located at the upper-left corner of the environment (cf. Figure 1). The seed device is not mobile, but has the same communication radius of r.

B. Gradient Algorithm (GA)

In the Gradient Algorithm proposed by Nagpal et al. [8], the seed device initiates a gradient by sending a message including an integer value of zero to its neighbors. This value is received by the neighbors of the seed node. Each neighbor takes the minimum value it received, increments it by one, and propagates it to its neighbors. This continues until all the devices in the environment have such a value assigned. This value is called the hop count h_i. When displaying the network taking the same color for each device that has the same hop count assigned the network looks like a wave of circular rings initiated from the seed where each ring has a width of approximately r (cf. Figure 1).

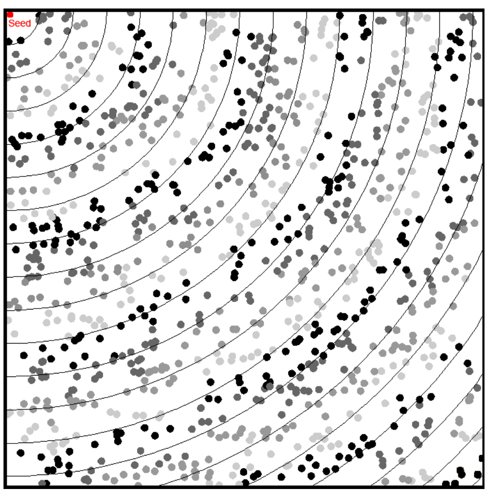


Fig. 1. Gradient field produced by GA. The rings are represented by different shades of Grey representing the same hop count values incrementing from the seed (top-left corner) to the bottom-right corner. (Same color in different rings is only for better visibility and does not indicate the same hop count)

C. Related Work

In order to estimate the distance between two nodes of a MANET with the GA, the minimum number of communication hops between the two nodes is counted and multiplied with the communication radius. [8] and [11] introduce two different techniques to improve the distance deduction from a gradient. In [8], an average of all communication hops in the node's neighborhood is calculated before multiplying with the radius. This improves the distance estimation as the position within a ring is corrected using the additional information about the hop count of all neighbors. Nevertheless, the error induced by sparse and unevenly distributed networks can still effect the distance estimation. In [11], the distance is calculated as a product of hop count and radius and then a manually chosen reduction rate is employed depending on the density of the neighborhood reducing the distance estimate of a node with few neighbors. This takes into account that in a sparse network, one communication hop usually has a length which is less than the radius. Both approaches locally correct the distance estimation but do not take into account that an overestimation of the length of one hop effects the following nodes. In addition, even in networks with consistent density one hop does not always correspond to the length of r. Moreover, mobility has not been considered in any of these scenarios. In [12], the effect of mobility on the distance estimation in a mobile ad hoc network is investigated with the result that mobility has a positive effect on the distance estimation. Different from the scenario presented here, the assumption is made that a node knows when it is moved and if so refreshes its own distance estimation before having a correcting effect on the surrounding nodes which leads to a general improvement within the network. This assumption matches a scenario in which new nodes enter a static network. The improvement of the distance estimation, thus, comes from an increased network density not from actual mobility effects.

III. Mobility

In this section, some mobility models from the literature [13] and some new ones are briefly studied in the following. Similar to [13], we categorize the mobility models into *individual* and *group mobility schemes*. Mobility models are applied to the devices with a certain probability at each cycle which is going to be analyzed in the experiments.

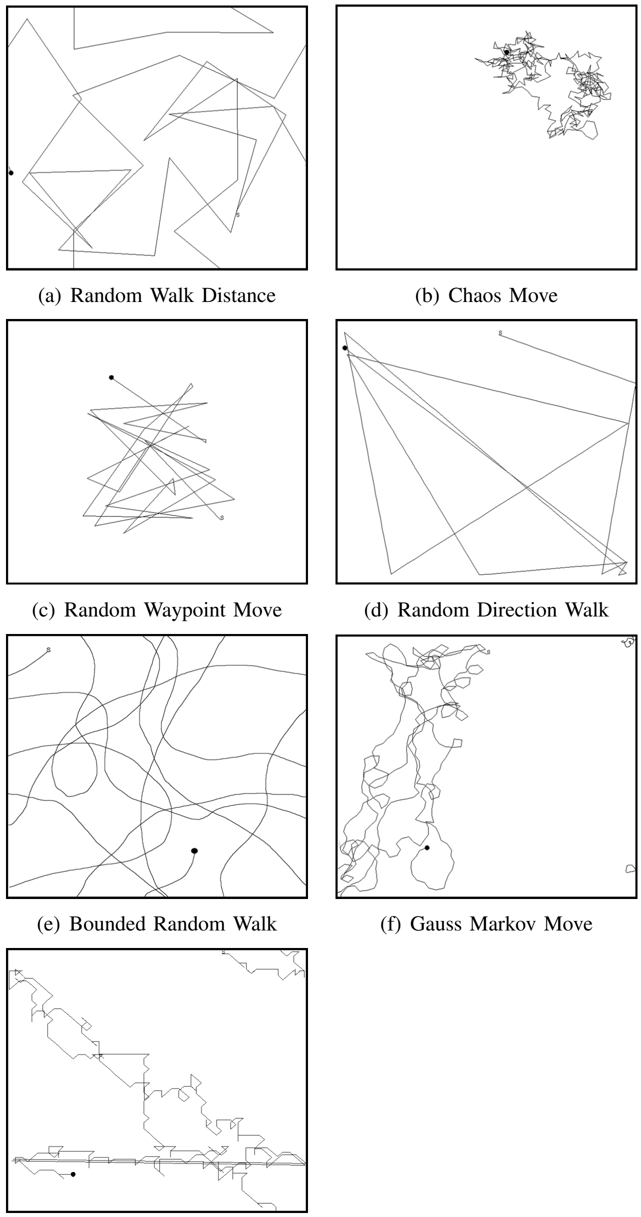
A. Individual Mobility Models

In individual mobility models, a node defines its next position independently from any other node in the system. Figure 2(a)-(g) shows trajectories of a node for the different moving models.

1) Random Walk: Similar to [13], every node selects a random direction and a random speed within allowed ranges and keeps on moving until a predefined distance is traveled or a predefined time has passed (Figure 2(a)). This mobility model is one of the most studied models in the literature e.g., [14].

2) Chaos Move: We slightly modify the above Random Walk model and let the nodes select a new random direction and speed "at each time step". This causes small movements as can be observed in Figure 2(b). This mobility scheme is supposed to keep the mobile devices in a small area around their starting position compared to the above Random Walk model.

3) Random Waypoint: By this mobility model, each node selects a random target position within the environment and a speed according to the allowed speed ranges. Once the node reaches the target, it pauses for a certain time, which is 10 cycles for all experiments, before it selects the next target position [13]. Also, the likelihood is high that they spend most of their time somewhere in the middle of the environment.



(a) Random Walk Distance (b) Chaos Move

(c) Random Waypoint Move (d) Random Direction Walk

(e) Bounded Random Walk (f) Gauss Markov Move

(g) Probabilistic Random Walk

Fig. 2. Trajectories for different individual mobility schemes

4) Random Direction Walk: In this mobility model, a node selects a random direction and a random speed within an allowed range and moves until it reaches the border of the simulation area. When the node reaches the border, it pauses for a certain time, which is 10 cycles for all experiments, before it selects another random direction. This move is a slight modification of the Random Waypoint model as the node selects its waypoints at the border of the environment. This avoids the extensive stays in the middle of the simulation environment.

5) Bounded Random Walk: Here, a node selects a random direction and a speed within some allowed range and moves for one time step. Then, it slightly alters its speed and direction by selecting new values within a small range around its old values. The difference between this mobility and the Chaos Move is that a mobile node moves more or less in the same direction as its original direction.

6) Gauss Markov Move: Similar to Bounded Random Walk, in this model [13], a node starts moving with a random direction and a speed within the allowed range. It moves for one step and then changes its direction and speed according to the following equations:

$$s_t = \alpha \cdot s_{t-1} + (1-\alpha) \cdot \mu_s + \sqrt{(1-\alpha^2)} \cdot s_g \quad (1)$$

$$d_t = \alpha \cdot d_{t-1} + (1-\alpha) \cdot \mu_d + \sqrt{(1-\alpha^2)} \cdot d_g \quad (2)$$

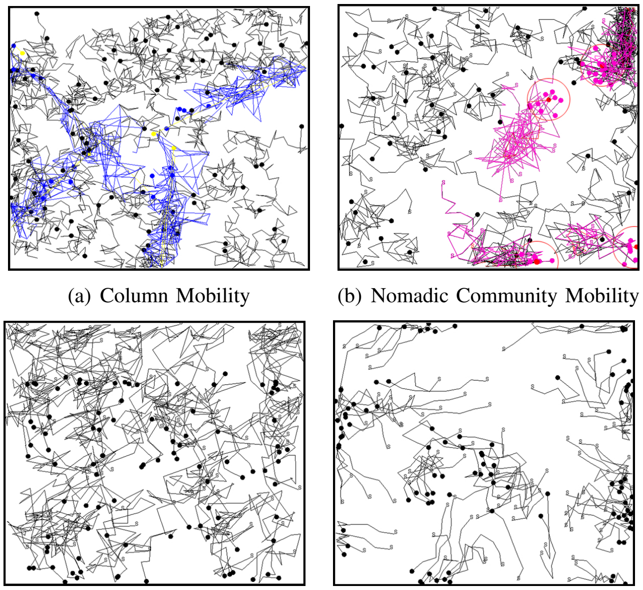
where s_t and d_t indicate the new values for speed and direction at time step t, respectively. α is a random parameter ($0 \leq \alpha \leq 1$) and s_g and d_g are chosen from a random Gaussian distribution with zero mean and standard deviation of one. μ_s and μ_d denote predefined constant average values for speed and direction such as 0.03 and 0.

7) Probabilistic Random Walk: In this move three possible states are defined separately for the movement in y-axis (left border) direction and x-axis (bottom border) direction. For the y-axis the node is either moving *backward*, *forward* or it *stands still*. For the x-axis the node is either moving *left*, *right*, or *stands still*.
There are fixed probabilities to transit from one state to the other and according to these probabilities the next move for the node is chosen. The probabilities emphasize moves that continue in the same direction. Also, movements between the previous and next positions without passing through the current location are prohibited. For the possible state transitions and probabilities see [13].

B. Group Mobility Schemes

In contrast to individual mobility models, group mobility models are characterized by mutual influences between the nodes. The specifics of one node's locomotion influence other nodes' next positions. These moving patterns seem more natural for the mobility within a swarm. Here several mobility models are adopted from [13] and the Stream mobility model is introduced. Figure 3(a)-(d) illustrates an example of the trajectories in a network of 100 nodes implementing the different group mobility models. Similar to the individual mobility schemes, the mobility is performed on the devices with a certain probability in each cycle.

1) Column Mobility Model: In the column mobility model, all nodes move randomly within the environment except for a configurable set of nodes (4 are shown in Figure 3(a)). Each set consists of a group leader and its followers. All followers move more or less in a row behind the leader simulating children that walk in a line while following their parent. The leader node moves according to the Random Walk model and each follower has a virtual reference point. The reference points are positioned in a row behind the leader. The reference points know their predecessors such that the first reference point in the row corresponds to the leading node. When the preceding reference point is moved, the following reference node takes



(a) Column Mobility (b) Nomadic Community Mobility

(c) Reference Point Group Mobility (d) Stream Mobility

Fig. 3. Trajectories for different group movement patterns

the last position of its predecessor. All following nodes can move randomly within their reference points' communication range. All nodes that do not correspond to a leader or follower move according to the Chaos Move.

2) Nomadic: The main idea of a nomadic mobility is to define some leaders (4 are shown in Figure 3(b)) that move according to the Chaos Move in the environment and collect followers. Whenever a node is within the signal range of a leader, it starts following the leader. That means the node can move randomly within the communication range of their leader but does not leave it. When a leading node has more than a predefined number of followers (20 nodes here), a randomly chosen node has to leave the group. This is a variation to the nomadic Community Mobility Model proposed by [13]. With the restriction on the number of followers it can be avoided that all nodes cluster around the leaders and the network might lose its connection to the seed. All none collected nodes move freely according to the Chaos Move.

3) Reference Point: In this model, each node has a virtual reference point and can move randomly within the communication range of its reference point just like in the Column Move model. At each step, all reference points are moved randomly but with the same direction and speed as like they are connected to each other. The movement of the reference net corresponds to the *Chaos Move* presented in III-A2.

4) Stream: We introduce the Stream Mobility Model to simulate streaming as if the devices were put into moving water or the wind would move them. Each node selects a random starting angle and a speed within an allowed range. When a node moves, it submits its angle to all its neighbors and the neighbors save the latest angle they receive from the others. When a node moves it uses this angle and modifies it by adding or reducing a randomly chosen degree between 0 and 30. Thus, each node's moving angle is influenced by the angle of its latest moved neighbor. This way, the nodes in a neighborhood, move more or less as in a stream. Figure 3(d) illustrates trajectories of the nodes.

IV. Error in Gradient Algorithm

As stated before many positioning concepts rely on a distance estimation derived from communication hops. The distance estimation procedure itself can vary (cf. section II-C) but it always depends on the assumption that the areas in which nodes have the same hop count form circular rings of approximately width r around the seed. To evaluate the robustness of such positioning concepts under mobility, the focus lies on the deviation of reality from this assumption.

A. Error Model

Considering a perfectly dense and evenly distributed ad hoc network each device (n) would have a hop count corresponding to $h^{ideal} := \lceil \frac{d(n,seed)}{r} \rceil$, where $d(n, seed)$ indicates the Euclidean distance between the node n and the seed. The area in which h^{ideal} would return the same value corresponds to the rings shown in Figure 1 and is further on called communication hop i, where i is the common value for h^{ideal}. As this is usually not the case, the deviation from this ideal case is computed for each node n as the difference between the ideal hop count[1] and the one obtained by the GA ($h(n)$) and the hop count assigned by the algorithm:

$$E(n) = h^{ideal} - h(n) \tag{3}$$

This deviation is further called the “hop count error”, aware of the fact that it is not really an error but rather a deviation from an ideal case. Since it makes a difference if the hop count assigned by the GA is higher or lower than the ideal hop count, a quadratic error is not considered. Similarly, the average error in a communication hop i can be computed as

$$E_i = \frac{1}{N_{h_i}} \sum_{j=1}^{N_{h_i}} (h_i - h(j)) \tag{4}$$

where j refers to all the nodes that are physically located in the communication hop i and N_{h_i} denotes the number of nodes in h_i. The overall error value is the average over all communication hops:

$$E = \frac{1}{M} \sum_{i=1}^{N_h} E_i \tag{5}$$

Here, M indicates the maximum number of communication hops.

1) Negative Error: As already stated, the density of the distribution of the nodes causes an error even in a static network (no mobility). A negative error means that we estimate a larger value for $h(n)$ than it must be. Figure 4 illustrates a simple example for a one-dimensional network. The left most node illustrates the seed and the gray scale colors show the different communication hops h_i. The error occurs in the

[1] Here, the exact position of the nodes needs to be known.

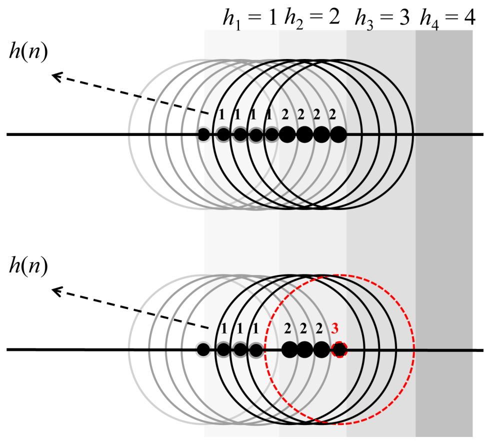


Fig. 4. An illustrative example for a negative error. The figure on the top contains no error, where the bottom figure shows a simple negative error.

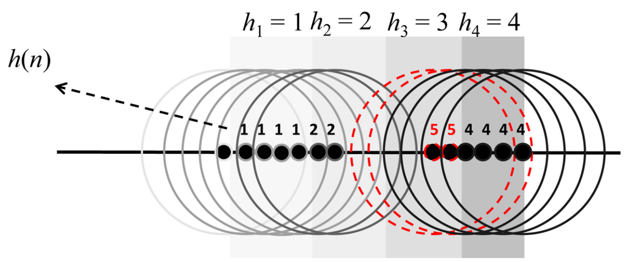


Fig. 5. An illustrative example for a high negative error

communication hop h_2 due to the gap in h_1. The node which is physically located in h_2 does not have any member of h_1 in its neighborhood and therefore its hop count is computed as 3. The error value in hop 2 is $E_2 = -\frac{1}{4}$. This error occurs due to low density in the neighboring communication hop with the smaller hop count value.

A similar but more fatal error occurs when the gap between two nodes is higher than the communication radius. Here, the node has no connection to nodes with lower hop count and therefore adapts its hop count to the neighbors with larger hop count values. An example for this situation is illustrated in Figure 5. The error occurs in the communication hop 3 and can be computed as $E_3 = -2$.

2) Positive Error: The negative error can dynamically occur and disappear within mobile networks as the gaps between nodes can become larger or smaller respectively.

By introducing mobility, a node does not know, if it has moved or its neighbors have moved. The nodes can only observe a change in the list of their neighboring nodes. Therefore, every node has to make sure that it updates its hop count value constantly. When a node with small hop count moves away from the seed into a communication hop with a larger hop count value, the nodes with larger hop count values might change their hop counts accordingly before the moved node has adapted its hop count to its new position due to asynchronous computation throughout the network. This phenomenon helps to reduce the negative error, by causing a counteracting positive error. Figure 6 illustrates this positive

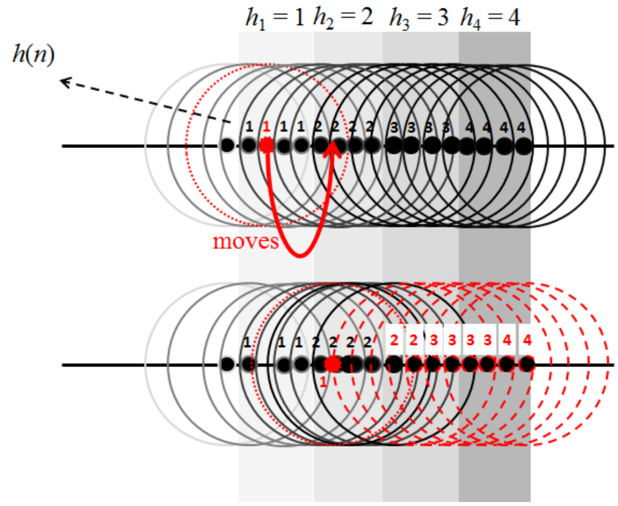


Fig. 6. An illustrative example for a positive error

error in an example. In this example, the positive error happens in communication hops 3 and 4 as $E_3 = \frac{2}{4}$ and $E_4 = \frac{2}{4}$. A drawback of mobility certainly is that the error values can change from negative to positive values, thus underestimating the distance from the seed. Nevertheless, even without realizing when a node has moved, as was the assumption in [12], the natural overestimation of distances might be corrected as an emerging effect of delayed computation and mobility.

V. Experiments

In the experiments, a mobile ad hoc network is simulated where a GA is initiated from one static node. The hop counts are measured for each node and averaged over each communication hop as described in IV-A. Different experiments are conducted using the mobility models presented in III. The goal of the experiments is to show that there is a relation between movement and hop count update which significantly improves the overall error. Also, we show that the different mobility models influence the optimal relation and the amount of the average error.

A. Parameter Settings

For the experiments, we select a 2-dimensional rectangular environment of size 1.0 x 1.0 units with 1000 nodes. The nodes are randomly positioned in the environment using a random uniform distribution. The seed node is placed in the upper left corner of the field and a communication radius r of 0.07 units is considered to be the same for all nodes. Based on the size of the environment and the value of the radius, we can have at most 21 communication hops[2]. A signal range of 0.07 units is selected as it corresponds to an average neighborhood size of 14 which is close to the critical minimum average neighborhood of 15 for the distance estimation presented in [8].

[2] $\lceil \sqrt{2}/0.07 \rceil = 21$

TABLE I
ERROR IN DIFFERENT COMMUNICATION HOPS (CHOP) FOR A STATIC NETWORK

CHop:	1	2	3	4	5	6	7
Avg. Error:	0	-0.38	-0.63	-0.9	-1.13	-1.39	-1.65
CHop:	8	9	10	11	12	13	14
Avg. Error:	-1.84	-2.09	-2.3	-2.52	-2.75	-2.98	-3.2
CHop:	15	16	17	18	19	20	21
Avg. Error:	-3.29	-3.47	-3.65	-3.83	-4.01	-4.07	-3.56

Preliminary experiments have shown that constructing a gradient field using 1000 nodes requires at most 30 cycles of the simulation run to be stable in a network without mobility. Therefore, we run the experiments for 130 simulation cycles and for the evaluations ignore the first 30 cycles. This way, we make sure that the gradient field is already built before analyzing the error. In one simulation cycle 1000 random nodes are executed. That means they first update their hop count and then possibly move according to the probability for movement p_m.

Experiments are repeated 50 times. The simulation environment is designed as a torus world, such that nodes can leave the environment and enter again at the opposite side. When a node leaves the environment its hop count is set to $unknown$, simulating a new node entering the environment on the other side.

For all movements the allowed speed range is selected as a random value between $\frac{r}{2} - 0.001$ units per cycle and $\frac{r}{2} + 0.001$ units per cycle, where r represents the communication radius. This way a node needs at least two steps to leave its own communication radius.

When a node is executed it can move with a probability of $p_m = 0, 0.1, 0.3, 0.5, 0.7, 1.0$. Here $p_m = 0$ indicates a static scenario without mobility. The implemented individual mobility schemes are Random Walk, Chaos Move, Random Waypoint, Random Direction Walk, Bounded Random Walk and Gauss Markov Move . For Random Walk, the maximum distance to move is selected as 0.6 units and maximum cycles to move is set to 10. In both Random Direction Walk and Random Waypoint a move is paused for 10 cycles. For Gauss Markov Move α is set to 0.75 and an average angle of 0 degree measured from the x-Axis of the environment (bottom border) is selected. Angle tolerance for Bounded Random Walk is set to 30 degrees.

In the Column Move, there are 10 leaders that are each followed by 10 nodes. The angle tolerance for Stream Move is set to 30 degrees.

B. Error in a Static Network

The first experiment concerns measuring the error value E_i for the 21 communication hops in a static network. The results are shown in table I. This confirms the error model in Section IV-A that in a static network the error is negative for all communication hops.

It can be observed that the negative error intensifies as the index of the communication hops increases. This indicates that an error which arises in one hop usually propagates through the following nodes.

Since the communication hops each contain a different number of nodes due to the nature of the scenario, from now on only the middle hops (10-15) are considered for further investigation as they contain a relatively high and similar number of nodes. Figure 7 illustrates the average number of nodes in different hops in a static network.

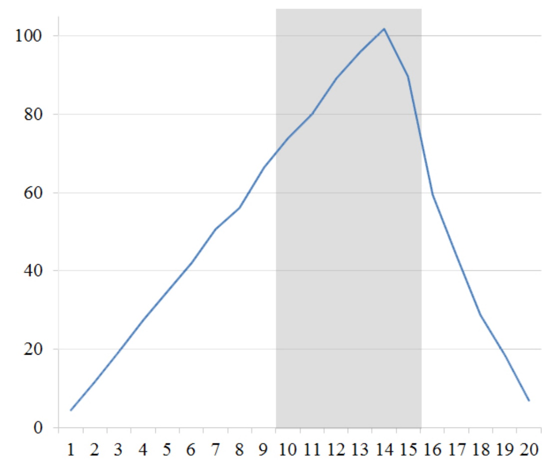


Fig. 7. Number of nodes in different communication hops in a static network

C. Mobile Network

In order to analyze the effects of mobility on the negative error, first the Random Walk individual mobility scheme is considered with different probabilities for movement p_m and compared to the results of a static network (Figure 8). We select Random Walk as a representative for individual movements since in preliminary experiments similar behaviors were observed for the other movements and Random Walk is one of the most studied mobilities in literature. The negative error from the static network is reduced even if only a small amount of mobility with 0.1 probability is employed. By 0.5 probability for a movement, the error rate is very close to zero for all the shown communication hops in Figure 8. The mobility rate of 0.7 already changes the error towards positive values which the effect of the positive error (cf. IV-A2) and with a probability of 1.0 a positive error effect of mobility is clearly observable.

As the mobility rate of 0.5 shows the lowest error values, we further analyze the mobility models with this probability rate.

D. Influence of individual mobilities

Figure 9 shows the average error for the individual mobility models except for the Random Waypoint Mobility as it has a high negative error. The is due to the fact that all of the nodes basically move in the middle of the field and after some cycles the network loses contact to the seed and the error decreases infinitely as shown in Figure 10. The moment when

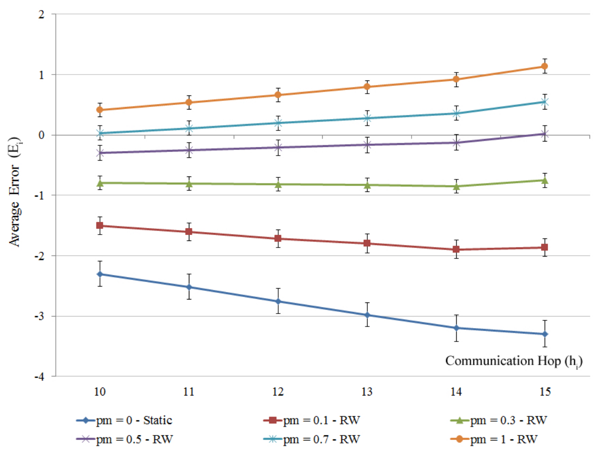


Fig. 8. Error in different communication hops when adding mobility to the network

the network lost the contact to the seed occurs later the less mobility we introduce.

As one can see, all the individual mobility models overcome the negative error of a static network. Furthermore, the error is quite constantly near zero for all five communication hops displayed. This shows that the compensation of positive and negative error works for each hop independently. This is an important observation that guarantees also an improvement in a hop count derived distance estimation. When looking at Figure 9 the Probabilistic Random Walk shows a noticeable higher positive error than the other mobility models. This can be explained by the character of the mobility model as all nodes are moved more or less into the same direction which leads away from the seed. As a positive error can only occur with movements in the opposite direction of the seed the positive error introduced by this move is higher than when using other mobility schemes.

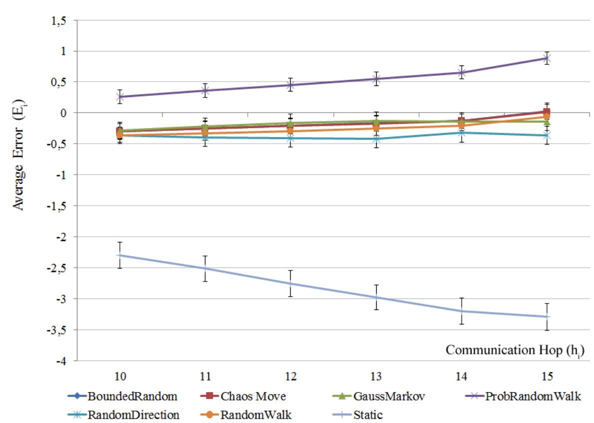


Fig. 9. Error with different individual mobility schemes

Among the other mobility models, Bounded Random, Gauss Markov, Chaos Move, Random Direction and Random Walk show very similar behavior in terms of error values. Although Random direction exhibits a slightly more negative behavior.

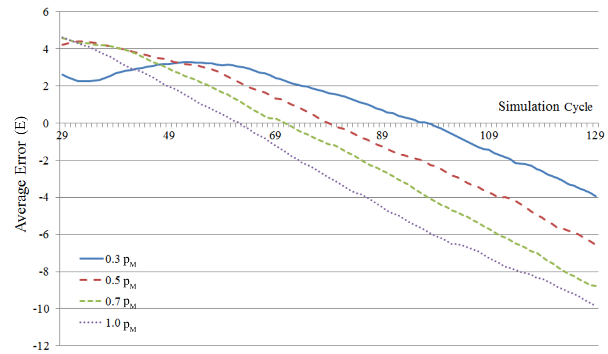


Fig. 10. Random Waypoint movement over time

We explain this with the pauses the nodes take as they come along the borders. This reduces the mobility over the observed period of time compared to the other mobilities which is accompanied by a reduced positive error influence.

From these results we conclude that the error rate of GA can be reduced in scenarios with independent individual movements. Our experiments reveal that positive error does not get dominant with a probability of $p_m = 0.5$ unless the movements mostly lead away from the seed. Furthermore a criterion was identified that implies whether a network lost its connection to the seed as in this case the negative error drifts to infinity. This criterion can even be monitored in each node in a decentralized way when knowing that the network has a more or less stable size. Also, it has been demonstrated that the relation between moving and updating the hop count influences the error compensation and it is crucial to find the right balance. In order to investigate these observations more in detail, we carry out experiments using group mobility schemes in the following.

E. Influence of group mobilities

Figure 11 shows the computed error values for the group mobility models. The Stream mobility model was designed to simulate similar movements within neighborhoods. When a node moves its direction and speed are similar to other nodes in the same region. Therefore, the adaptation a node has to make to the hop count is also similar for nodes in the same neighborhood. This seems to have a positive effect on the error as can be seen in Figure 11. The same effect can be observed in the Nomadic move. As one group moves together through the network the error seems to be less volatile. As already shown for the Probabilistic Random Walk another important factor for the development of the error is the direction of a move relative to the hop count rings. Both in the Stream move as well as the Nomadic move the groups move quite randomly through the network. The mixture of movements leading away or towards the seed lead to less positive error as for example the movements in the Column Move, where the groups keep moving in more or less the same direction (cf. Figure 3(a)). Next to the Column Move, the Reference Point Move also shows a high positive error. This can be explained

by the additional movement that is introduced by moving the reference point network as well as each node individually. This additional movement increases the error rate (cf. Figure 11).

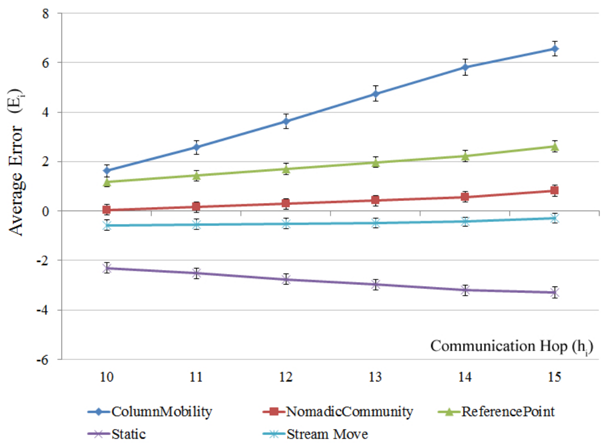


Fig. 11. Error with different group mobility schemes

The examined group mobility models confirm the observation that the direction of the movements influence the error rate in a network. Moreover, the results for the Reference Point Move indicate that speed might also be an influencing factor for the level of positive error that arises through mobility.

F. Discussion

The experiments in this paper show that introducing a certain mobility into a network has a positive effect on the hop count error. It seems that updating the hop count twice before moving yields the best results in overcoming the natural overestimation of distances in the scenario presented here. It has been shown that the way nodes move relative to each other is an important factor. A similar movement of adjacent nodes seems to lead to a smoother compensation of positive and negative error. Also the direction of the movement with respect to the position of the seed plays an important role, as a positive error can only arise from movements orthogonal to the seed.

VI. Conclusion and Future Work

This paper is about experimental analysis of different error models in GPS free mobile ad hoc networks. The goal is to obtain an understanding of the hop count distribution in the presence of different mobility models in an ad hoc network. Particularly, an error model is defined and computed for the GA, which is a basic element for computing coordinate systems in GPS free environments. The hop count error reflects the variance in the length of one hop count in a MANET due to node distribution, mobility or density. The experiments and analysis indicate that with mobility of even low rates, the error can be reduced. Nevertheless, a high degree of mobility as well as certain characteristics of the movements can lead to an overcompensation of the natural negative error. The direction of the movements with respect to the seed as well as the relative movement in neighboring regions play an important role for the impact mobility has on the hop count error.

In future work, it would be interesting to investigate the impact of different movement speeds on the hop count error as an increased speed might have similar effects as the additional movement of the reference network in the Reference Point Move. Also, as stated before, the degree of movement is crucial for the compensation of positive and negative error. It would be helpful to find decentralized metrics that capture critical characteristics of the movement such as direction, deviation of angle and speed within regions of the network, or the level of change caused by a move since the last update. If one would succeed in determining how the movement changes the network's structure, it might be possible to dynamically correct the hop count derived distance estimation in each node. This could be investigated in the future to improve the robustness of any GA based application such as building a coordinate system.

References

[1] IETF. (2011) Manet working group website. [Online]. Available: http://datatracker.ietf.org/wg/manet

[2] D. Coore, "Botanical computing: A developmental approach to generating interconnect topologies on an amorphous computer," Ph.D. dissertation, MIT Department of Electrical Engineering and Computer Science, 1999.

[3] R. Nagpal, "Programmable self-assembly: Constructing global shape using biologically-inspired local interactions and origami mathematics," Ph.D. dissertation, MIT Department of Electrical Engineering and Computer Science, 2001.

[4] C. Maihofer, "A survey of geocast routing protocols," *Communications Surveys Tutorials, IEEE*, vol. 6, no. 2, pp. 32 –42, 2004.

[5] M. Mamei and F. Zambonelli, "The cloak of invisibility: Challenges and applications," *IEEE Pervasive Computing*, vol. 1, no. 4, pp. 62–70, 2002.

[6] R. Nagpal, "Organizing a global coordinate system from local information on an amorphous computer," *A.I. Memo No. 1666, MIT*, 1999.

[7] D. Coore, "Establishing a coordinate system on an amorphous computer," *Workshop on High Performance Computing*, 1998.

[8] R. Nagpal, H. Shrobe, and J. Bachrach, "Organizing a global coordinate system from local information on an ad hoc sensor network," in *Proceedings of the 2nd International Workshop on Information Processing in Sensor Networks (IPSN '03)*, ser. Lecture Notes in Computer Science LNCS 2634, 2003, pp. 333–348.

[9] M. Mamei and F. Zambonelli, "Tuples on the air (tota)," in *Field-Based Coordination for Pervasive Multiagent Systems*, ser. Springer Series in Agent Technology, T. Ishida, N. Jennings, and K. Sycara, Eds. Springer Berlin Heidelberg, 2006, pp. 119–155.

[10] C. Nüsslein-Volhard, "Gradients that organize embryo development," *Scientific American*, vol. 275, no. 2, pp. 54–55; 58–61, 1996.

[11] S. Y. Wong, J. G. Lim, S. V. Rao, and W. K. G. Seah, "Density-aware hop-count localization (DHL) in wireless sensor networks with variable density," in *In Proceedings of the 2005 IEEE Wireless Communications and Networking Conference (WCNC)*, vol. 3. IEEE Computer Society, 2005, pp. 1848– 1853.

[12] J. G. Lim and S. V. Rao, "Mobility-enhanced positioning in ad hoc networks," in *In Proceedings of the 2003 IEEE Wireless Communications and Networking Conference (WCNC)*, vol. 3. IEEE Computer Society, 2003, pp. 1832–1837.

[13] T. Camp, J. Boleng, and V. Davies, "A survey of mobility models for ad hoc network research," *Wireless Communications and Mobile Computing, Special Issue on Mobile Ad Hoc Networking*, vol. 2, pp. 483–502, 2002.

[14] M. M. Zonoozi and P. Dassanayake, "User mobility modeling and characterization of mobility patterns," *IEEE Journal on Selected Areas in Communications*, vol. 15, no. 7, pp. 1239–1251, 1997.